Harnessing Big Data for Predictive Analytics in Bariatric Surgery

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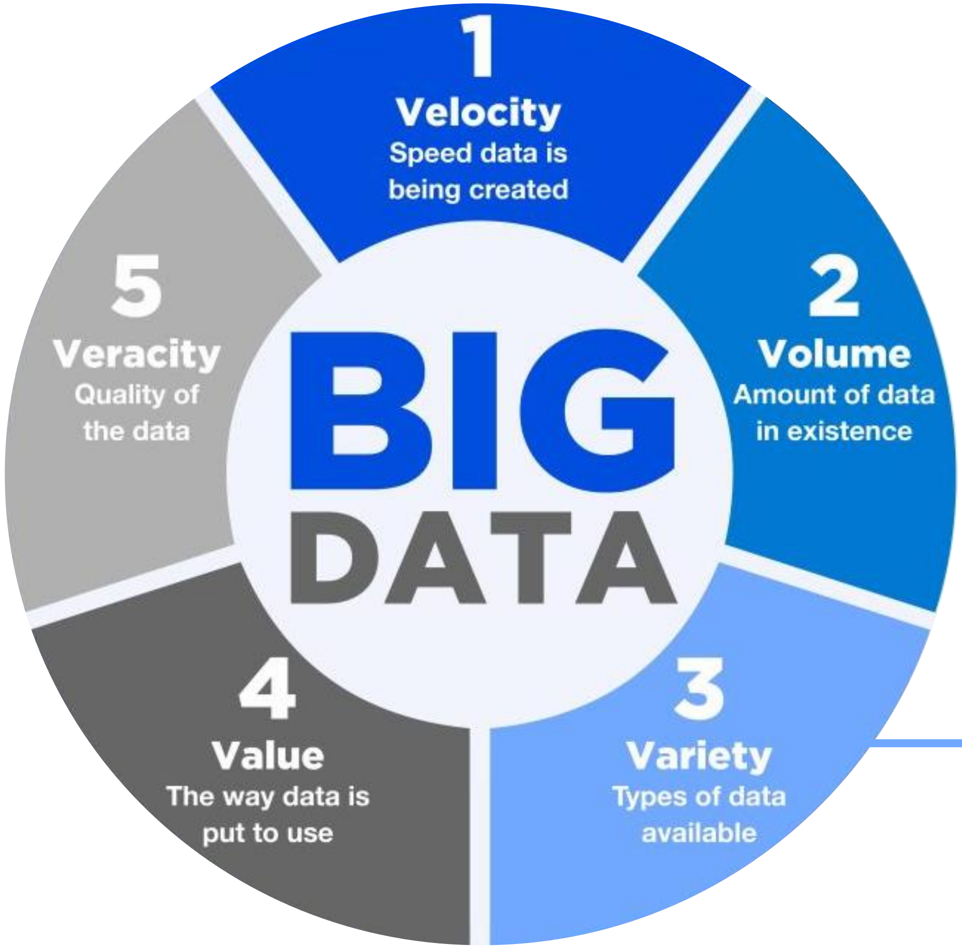
I have no potential conflict of interest to report

Background



"diverse, complex, disorganized, massive, and multimodal data generated by researchers, hospitals, and mobile devices around the world"

- Clinical data
- Imaging
- Pathology
- Phenotype
- Genetics
- Molecular
- Behavioral

Use of Big Data in Bariatric Surgery

Robotics and MIS

“Computer-assisted surgery”
Algorithms utilized to increase precision and safety (i.e. stapling)

Operational Efficiency

Optimize surgical workflows and resource allocation

Personalized Medicine

Tailor treatment based on risk stratification, determine who needs more intensive follow-up or dietary support

Large datasets can uncover hidden patterns, correlations, trends, and insights to enhance quality and efficiency of surgical care

Preoperative Planning	Patient-level Prediction	Real-Time Monitoring	Postoperative Care
Shared decision-making: surgery type. Pre-op risk mitigation (leak, bleed, VTE)	Regression Models/ ML Models: Weight loss outcomes, Comorbidity resolution, Surgical complications, Weight Regain, Nutritional Deficiency Risk	Actionable insight for intraoperative decisions: Monitoring to avoid prolonged hypotension	Track recovery, incorporate early intervention, predict risk of readmission or complications, behavioral prediction/adherence

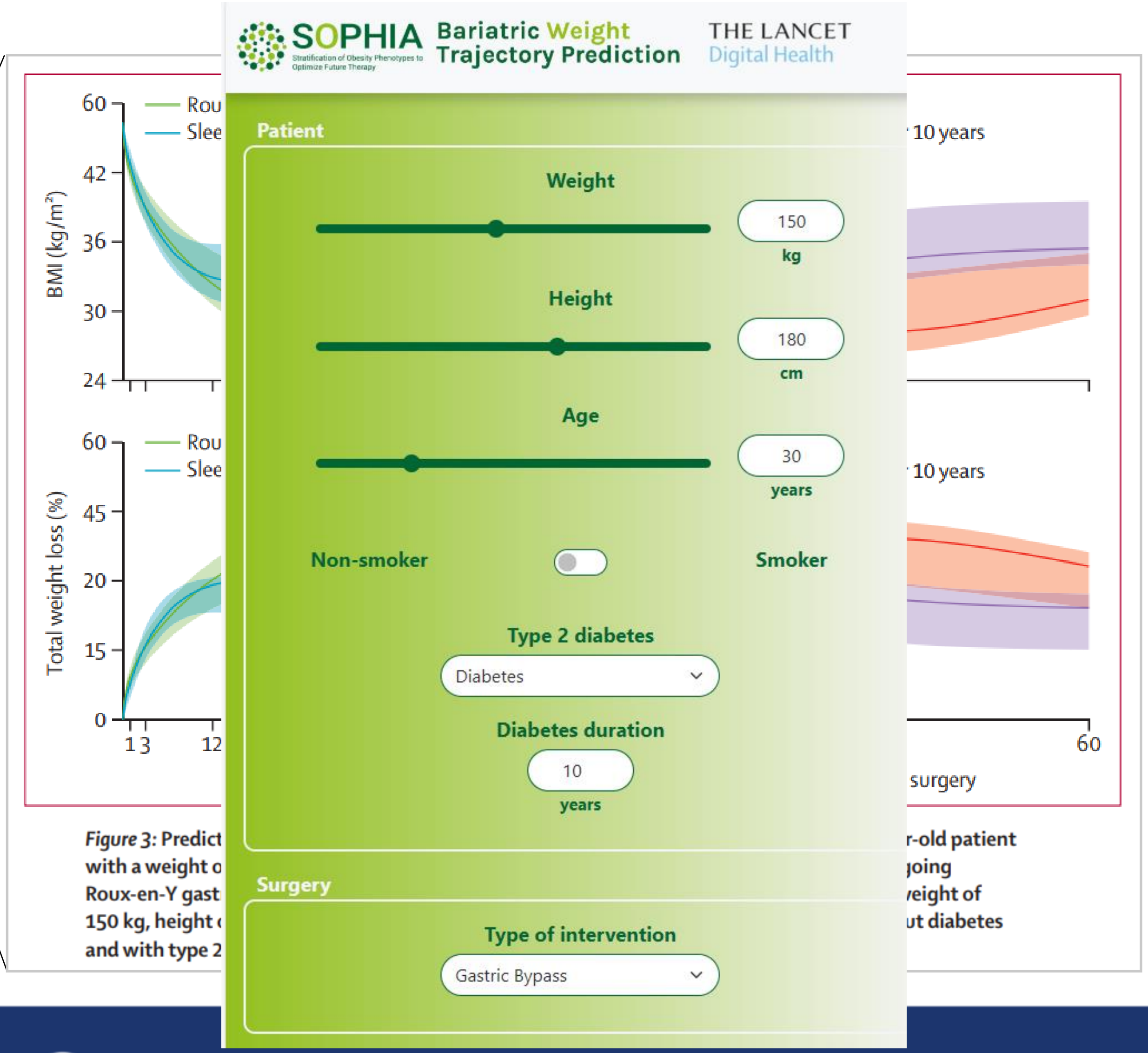
Predictive Analytics for Weight Trajectory – The SOPHIA Study

Outcome: 5-year weight trajectory after sleeve & bypass

LASSO regression for feature selection; Decision Tree (ML) analysis
Classification and Regression Trees (CART) algorithm
80/20 with internal validation (n=1493, France)
External validation in 8 other cohorts (n=7137 Europe, n=167 Americas, n-977 Asia), including SLEEVEPASS and SM-BOSS (n=457)

Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort SOPHIA study

Patrick Saux*, Pierre Bauvin*, Violeta Raverdy, Julien Teigny, Hélène Verkindt, Tomy Soumphonphakdy, Maxence Debert, Anne Jacobs, Daan Jacobs, Valerie Monpellier, Phong Ching Lee, Chin Hong Lim, Johanna C Andersson-Assarsson, Lena Carlsson, Per-Arne Svensson, Florence Galtier, Guelareh Dezfoulian, Mihaela Moldovanu, Severine Andrieux, Julien Couster, Marie Lepage, Erminia Lembo, Ornella Verrastro, Maud Robert, Paulina Salminen, Geltrude Mingrone, Ralph Peterli, Ricardo V Cohen, Carlos Zerrweck, David Nocca, Carel W Le Roux, Robert Caiazzo, Philippe Preux, François Pattou



AI and Machine Learning can be used to predict "success" after surgery

Original Research Article

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Application of machine learning algorithms in classifying postoperative success in metabolic bariatric surgery: Acomprehensive study

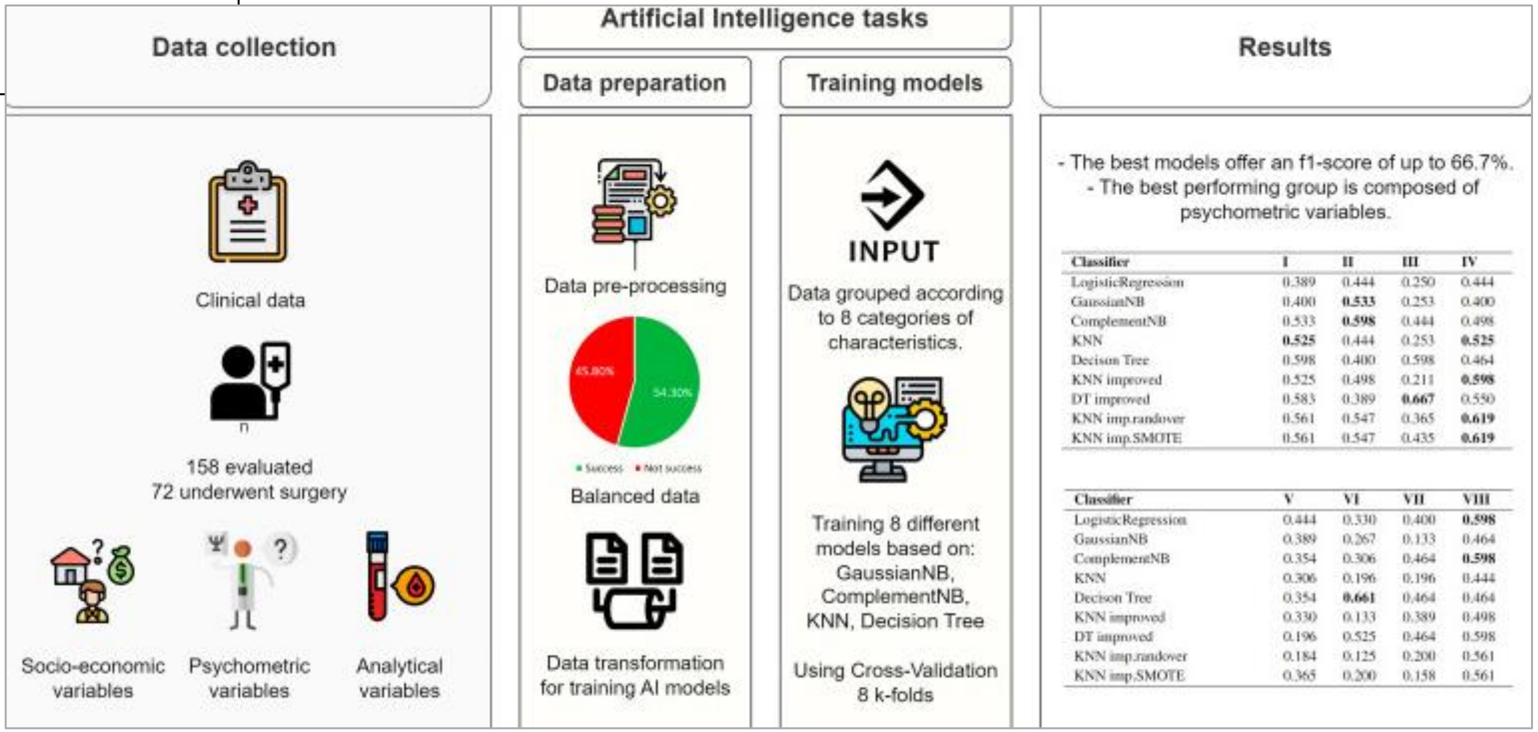
José Alberto Benítez-Andrades[1], Camino Prada-García[2,3], Rubén García-Fernández[4], María D Ballesteros-Pomar[5], María-Inmaculada González-Alonso[4] and Antonio Serrano-García[6]

Incorporation of socioeconomic, psychometric, and lab values into ML models for "success" (>50%EWL) after surgery:

- *54.2% of cohort had "successful" weight loss*
- highlight the **multifactorial complexity** in predicting success

Table 1. Division of input variables into groups.

Group	Description
Group I	Socio-economic variables
Group II	Psychometric variables
Group III	Analytical variables
Group IV	Only psychometric variables from the EuroQoL5 Quality of Life Scale
Group V	Only the psychometric variables from the Salamanca screening questionnaire
Group VI	Only the psychometric variables from the ACTA Inventory of motivation for change
Group VII	Combination of all variables (Groups I, II, and III)
Group VIII	Combination of socio-economic variables (Group I) and psychometric variables (Group II)



Classifier	I	II	III	IV
LogisticRegression	0.389	0.444	0.250	0.444
GaussianNB	0.400	**0.533**	0.253	0.400
ComplementNB	0.533	**0.598**	0.444	0.498
KNN	**0.525**	0.444	0.253	**0.525**
Decison Tree	0.598	0.400	0.598	0.464
KNN improved	0.525	0.498	0.211	**0.598**
DT improved	0.583	0.389	**0.667**	0.550
KNN imp.randover	0.561	0.547	0.365	**0.619**
KNN imp.SMOTE	0.561	0.547	0.435	**0.619**

Classifier	V	VI	VII	VIII
LogisticRegression	0.444	0.330	0.400	**0.598**
GaussianNB	0.389	0.267	0.133	0.464
ComplementNB	0.354	0.306	0.464	**0.598**
KNN	0.306	0.196	0.196	0.444
Decison Tree	0.354	**0.661**	0.464	0.464
KNN improved	0.330	0.133	0.389	0.498
DT improved	0.196	0.525	0.464	0.598
KNN imp.randover	0.184	0.125	0.200	0.561
KNN imp.SMOTE	0.365	0.200	0.158	0.561

Use of claims data for modeling resolution of diabetes:

Decision-Analytic Modeling: Past, Present, and Future

Using Machine Learning Applied to Real-World Healthcare Data for Predictive Analytics: An Applied Example in Bariatric Surgery

Stephen S. Johnston, MA,[1,*] John M. Morton, MD,[2] Iftekhar Kalsekar, PhD,[1] Eric M. Ammann, PhD,[1] Chia-Wen Hsiao, MPH,[3] Jenna Reps, PhD[4]

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22,099 candidate predictors in dataset →
125 predictors selected via LASSO regression

3 predictors w strongest NEGATIVE association with cessation of antihyperglycemic meds:

1. baseline use of insulin
2. prior LAGB
3. increasing Diabetes Comorbidity Severity Index

3 predictors w strongest POSITIVE association with cessation of antihyperglycemic meds:

1. Non-insulin glucose lowering meds
2. RYGB (vs. Sleeve)
3. younger age

Figure 4. Receiver operating curve plot for the external validation of the model in Optum (N = 3477).

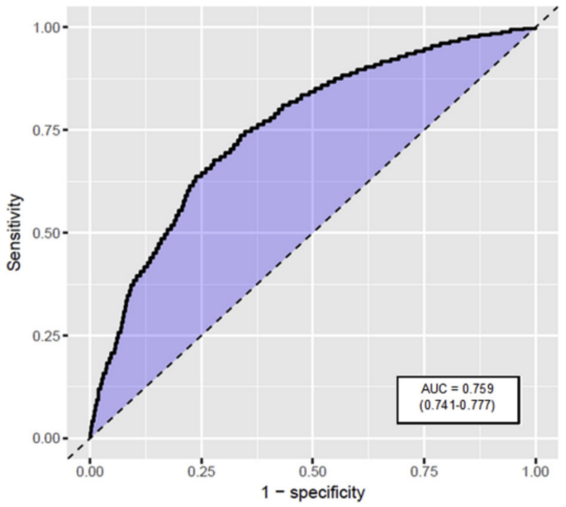
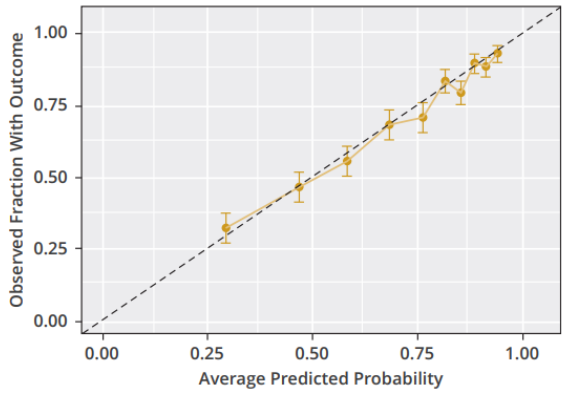


Figure 5. Calibration* plot for the external validation of the model in Optum (N = 3477). *The sample was split into 10 deciles, and the mean predicted probability of the outcome was plotted against the observed probability of the outcome for each decile. The dotted line represents perfect model calibration, with the expected risk neither under- nor overestimated across risk deciles.



Predictive analytics may be useful BUT external validation is needed

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https://doi.org/10.1007/s11695-021-05548-x

REVIEW

A Scoping Review of Artificial Intelligence and Machine Learning in Bariatric and Metabolic Surgery: Current Status and Future Perspectives

Athanasios G. Pantelis[1] · Georgios K. Stravodimos[1] · Dimitris P. Lapatsanis[1]

…**iterative process**, collecting more data from a relevant patient cohort to better train algorithms to ultimately help guide patient and physician decision-making

Obesity Surgery (2022) 32:2772–2783
https://doi.org/10.1007/s11695-022-06146-1

REVIEW

Artificial Intelligence in Bariatric Surgery: Current Status and Future Perspectives

Mustafa Bektaş[1] · Beata M. M. Reiber[1] · Jaime Costa Pereira[2] · George L. Burchell[3] · Donald L. van der Peet[1]

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*"Due to the **missing external validation** in most studies, the **first step for future studies in bariatric surgery** should be the inclusion of external validation cohorts to **gain more generalizability** of machine learning models"*

Challenges and Future directions:

Needs for ethical and safe deployment of predictive models:

- Enhanced data quality and standards
- Strict reporting systems and governing bodies
- Objective benchmarking
- Multicenter institutional data collection for **external validation**

Future projects may include:

- Revealing hidden relationships between ALL phases of bariatric patient management (perioperative, intraoperative, postoperative)
- Variety of data streams and inputs for diverse generalizations
- Decision-making support
- improving the predictive accuracy of existing models

Conclusions:

- **Big data transforms bariatric surgery through personalized treatment and optimized outcomes**
  - Integration **of real-time data** can **enhance decision-making** and **patient monitoring**
  - Predictive analytics and AI **can improve surgical precision** and **post-operative care strategies**
  - Clinical decision support systems **optimize treatment plans** based on real-time analytics
  - Diverse data integration (e.g., genomics, imaging) **enhances patient profiling and treatment customization**
- **Population health management strategies leverage big data for preventive interventions**
- **Ethical guidelines and regulatory frameworks ensure responsible data use and patient consent**
- **Collaboration and data sharing drive research advancements and innovation in bariatric surgery**

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